



SIGFIRM Working Paper No. 9

## Looking Underwater in the Lab

Jean Paul Rabanal, University of California, Santa Cruz

August 2012

SIGFIRM-UCSC  
Engineering-2, Room 403E  
1156 High Street  
Santa Cruz, CA 95064  
831-459-2523  
Sigfirm.ucsc.edu



The **Sury Initiative for Global Finance and International Risk Management (SIGFIRM)** at the University of California, Santa Cruz, addresses new challenges in global financial markets. Guiding practitioners and policymakers in a world of increased uncertainty, globalization and use of information technology, SIGFIRM supports research that offers new insights into the tradeoffs between risk and rewards through innovative techniques and analytical methods. Specific areas of interest include risk management models, models of human behavior in financial markets (the underpinnings of “behavioral finance”), integrated analyses of global systemic risks, and analysis of financial markets using Internet data mining

# Looking underwater in the lab

Jean Paul Rabanal \*

University of California, Santa Cruz

November, 2011

## Abstract

The timing of default can greatly affect an individual's wealth. This paper empirically studies the optimal stopping decision —default— where subjects have the alternative to stop paying a loan on the asset whose value is governed by the Brownian motion. The optimal policy is to stop when the asset value crosses the optimal threshold defined by a real deferral option, where the deferral option value depends on the volatility as well as the actions of others. Surprisingly, I find that subjects follow the theoretical predictions of the model. The neighbors effect turns out to be less important in the high volatility treatments, but in the low volatility treatments, the presence of neighbors leads to a higher rate of default.

**Keywords:** Real options, optimal stopping, laboratory experiment

**JEL codes:** G13, D83, C91

---

\**Email:* jprabana@ucsc.edu *Address:* Engineering 2, 401 Santa Cruz, CA 95064 *Tel:* 1-831-459-5774 *Fax:* 1-831-459-5077. I would like to thank Dan Friedman, Ryan Oprea, Ai-ru Cheng, James Pettit, Olya Rud and Sean Tanoos, and seminar participants at UCSC, CREED at University of Amsterdam, Max Planck Institute of Economics, University of Munich and VGSE at University of Vienna for their invaluable comments and support. This research was also supported by funds granted by SIGFIRM at the University of California, Santa Cruz.

# 1 Introduction

Approximately one in four households in the United States is currently “underwater” (First American CoreLogic, 2010), owing more on a mortgage than the house is worth. In times of crisis, the decision to default or refinance becomes crucial to protecting the wealth of the individual. Recent evidence shows that the median household defaults when the equity-to-value ratio falls to -62 percent. This paper aims to understand the underlying factors of the individual stopping decisions.

Past literature has focused on the causes and the consequences of the strategic decision to default, using field data. This paper departs from existing literature on mortgage default in two ways. First, we build a simple environment that characterizes the borrower’s optimal decision to default. An agent can stop the mortgage payments (interest plus principal) by incurring a quit fee anytime before the end of the game. Second, we test the predictions in a laboratory experiment. The advantage of this approach is that it allows us to observe and control how human subjects react to key variables that are unobservable in field data.

The theoretical foundation of this paper is related to the study of deferral options defined as the right, but no the obligation, to take an action at a pre-determined cost, for a pre-determined period of time. In the context of the mortgage market, the borrower has the choice of continue to pay his obligation or exercise the right to default —the option. My conjecture is that human subjects will defer their decision to default long enough such that the asset price is lower than their liabilities, i.e. they will default when they are underwater. In the laboratory, I can control different values of the deferral option, e.g. asset volatilities, and observe how human subjects will respond. We also incorporate a neighbors effects into our analysis, thus allowing for contagion effects to be a part of the decision to default. While recent literature has estimated the contagion effects, there have been some difficulties with its identification.

The next section locates the contribution of this paper in the existing literature. In particular, it emphasizes that there has been a gap between the theoretical models of defaulting and field evidence. The latter cannot properly identify the value of the deferral option. However, in the laboratory, it is possible to quantify its value given that the asset generation process is known.

Section 3 lays the theoretical foundation. After describing the basic assumptions, it presents the problem faced by the subject in the decision to default. Next, a numerical solution is presented, specifying the asset price that triggers default. The agent should continue to pay the financial obligation as long as the asset price is greater than the optimal threshold.

Section 4 contains the testable predictions based on the conjecture that actual behavior will approximate optimal behavior, i.e. subjects will defer their decision until they are

sufficiently underwater. It also presents the experimental design. The experimental design is two-by-two. The first level corresponds to asset price volatilities —low and high— and the second level considers the presence of neighbors effect —independent and dependent. The experiment involves 100 human subjects and each subject is assigned to one of the four different treatments.

Section 5 presents the results. They generally support the predictions with some important qualifications. The impact of neighbors is not important in the high volatility treatments, but in the low volatility treatments the presence of neighbors leads to higher rate of default.

Finally, section 6 concludes with a discussion of results and suggests possible venues of future research.

## 2 Related literature

The literature on mortgage default has focused on two hypotheses behind default. The first hypothesis is known as a “ruthless” or “strategic default.” According to this hypothesis, default occurs when a borrower’s equity falls below some threshold amount and the borrower decides that the cost of paying back the mortgage (liability) outweighs the benefits of paying and holding on to the asset. In financial terms, this decision can be characterized as a put option. The borrower decides to give up the asset when the spot asset price is sufficiently lower than the strike price, known as the mortgage obligation.<sup>1</sup> The option to default can also be interpreted as a deferral option. Dixit and Pindyck (1994) elaborate on this interpretation in their textbook “Investment under uncertainty.” The agent will make the irreversible investment decision once the project values surpasses the total cost, which includes the material fixed cost plus option value. Deferring the decision has a positive value because exercising the option today implies that it cannot be done later.

The second hypothesis complements the first one and is known as the “double trigger” hypothesis. Default occurs following a negative income shock. Some researchers have recently emphasized that there may be other non-monetary variables that affect the decision of “walking-away” and could also be considered as part of the second hypothesis, as an additional cost to default —moral or social. White (2009) argues that the media and political institutions shape the opinion regarding default. Guiso, Sapienza, and Zingales (2009) show that 81 percent of respondents answered positively to the question, “Do you

---

<sup>1</sup>Default, as part of the early termination of the mortgage contract, affects the valuation of the mortgage. In general, early termination of the mortgage is due to two factors: prepayment and default. The former is treated as an American call option and the latter as an European compound put option. See Kau, Keenan, and Taewon (1994) for the valuation of mortgages and Vandell (1995) for a early review on the literature of mortgage default.

think that is morally wrong to walk away from a house when one can afford to pay the monthly mortgage? "

The empirical studies test both explanations using mortgage default data. These studies incorporate survival analysis, a well-known tool in statistics use to study death in biological organisms and failure in mechanical systems. The goal is to estimate the hazard function, which is defined as the probability of default at a particular time conditional on survival, i.e. the household has not yet defaulted on the mortgage. The hazard function includes variables that capture the idea behind the strategic default hypothesis, such as loan-to-value (LTV) and another set of variables related to the double trigger hypothesis; e.g. unemployment, credit utilization or credit scores. To compute the LTV, household liability data are available from private and public agencies.<sup>2</sup> The liabilities are discounted at market interest rates. The other component used to construct the LTV variable is the asset value, which is approximated by repeated-sales indices (e.g. Case-Shiller).<sup>3</sup>

A recent study by Bhutta, Dokko, and Shan (2010) sheds additional light on the level of equity (assets minus liabilities) that triggers default after controlling for liquidity issues. Working with non-prime first-lien home purchase mortgages<sup>4</sup> originated in 2006 with a combined LTV of 100 percent in the states of Arizona, California, Florida and Nevada, the authors found that the median borrower does not strategically default until the equity-to-value ratio is negative 62 percent. Notice that testing the strategic behavior by considering the LTV variable is not sufficient. A strategic agent will also consider the foregone opportunity of exercising the option to default later. In an experimental set-up, it is feasible to measure the option value and therefore adequately test the financial theory.

Besides the traditional hypotheses discussed, recent studies have also emphasized contagion effects. These effects can be present via social norms or material incentives. Chan, Gedal, Been, and Haughwout (2010) find that mortgage holders, living in the New York City area with high foreclosure rates and high real state owned (REO) activity, have a substantially greater risk of falling behind on the mortgage, as do mortgage holders living in predominantly black neighborhoods. Campbell, Giglio, and Pathak (2009) show that foreclosure at a distance of 0.05 miles lowers the price of a house by approximately one percent in the state of Massachusetts. Using survey data, Guiso, Sapienza, and Zingales

---

<sup>2</sup>Alternatively, the empirical studies also consider the equity-value-ratio instead of the LTV. In case that there is more than one loan, it is convenient to use the combined loan-to-value ratio (CLTV).

<sup>3</sup>There are several empirical papers that deal with the impact of equity and financial variables in the default or prepayment decisions. Depending on the time of analysis, authors consider these two decisions simultaneously by estimating hazard functions with competing risks. See Deng, Quigley, and Order (2000), Foote, Gerardi, and Willen (2008), Bajari, Chu, and Park (2008), Pennington-Cross and Ho (2010) and Gerardi, Shapiro, and Willen (2007).

<sup>4</sup>In the financial jargon, the terms non-prime and subprime mortgage loan are used indifferently. A *subprime mortgage loan* is a residential mortgage loan that is particularly risky for some reason. The elevated risk may stem from the credit history of the borrower, the lack of a large down payment, or a monthly payment that is large relative to the borrower's income (Foote and Willen 2011).

(2009) find that people who know someone who defaulted strategically are 82 percent more likely to declare their intention to do so.

Identifying social interactions effects in the field data has proved to be cumbersome (Manski 1993). Some of the principal issues in identifying the impact of social interactions include: (i) controlling for correlated effects that affect all group members similarly, (ii) controlling for contextual effects such as social background characteristics of group members, and (iii) controlling for self-selection issues. The results in Chan, Gedal, Been, and Haughwout (2010) are indicative of endogenous interactions —neighborhoods with high foreclosure rates are more likely to fall behind on their mortgages. However, it is not clear whether this is due to endogenous or correlated effects. Given these difficulties, laboratory experiments appear to be a perfect environment for studying social interactions.

This paper is not the first to study deferral options in the laboratory. Some recent studies have focused on testing irreversible investment decisions —call options— inspired by Dixit and Pindyck (1994). The project value follows a random process and the subject incurs a fixed cost to seize the irreversible investment opportunity. List and Haigh (2010) work in a two-period model using a simple design. A set of contracts is offered to the subjects, and each contract specifies two alternatives: invest today or tomorrow. Their results indicate that undergraduate subjects, as well as professional traders, choose the correct alternatives according to the theoretical predictions of the option model.

In a finite horizon environment, Oprea, Friedman, and Anderson (2009) design a stochastic model with three different asset volatilities (high, medium and low). They show that undergraduate subjects follow the option model in the low treatment. Subjects in other treatments invest at values below optimum, but with predicted ordering. The authors also find evidence of learning behavior where subjects learn to invest in low and medium treatments. The present paper has similar features but also incorporates the neighbors effect. The next section describes the environment and the optimal asset price that triggers default.

### 3 Environment

The environment will focus on the borrower’s decision and does not consider the borrower’s solvency or ability to service the debt. The agent needs an asset to get a certain level of felicity  $\Theta$  and benefits from the asset by being an owner or a renter. The asset, with value  $H$  varying randomly, has been acquired with an initial loan ( $L_0$ ) with loan-to-value equal to one. The objective is to identify the timing of the agent’s decision to switch from being an owner to becoming a renter.

The characteristics of the loan are as follows: interest rate payments are made in each

period with the principal paid at the end of the game. The agent decides to stop paying the loan if such course of action increases the expected payoff. The decision to stop involves a fixed cost that can be interpreted as an upfront lease or transaction cost. The agent receives a reward ( $B$ ) conditional on remaining an owner throughout the game.  $B$  may depend on the decision of other agents —assumed to be constant for now.

### 3.1 Payoffs and objective function

The payoffs correspond to the decision: to stop or not to stop. The agent is not allowed to default in the last period. Therefore, the terminal payoff consists of the asset value plus the reward, less the financial obligation

$$H_T - L_0 + B \quad (1)$$

where  $H_T$  is the asset price at the end of period,  $L_0$  is the loan principal and  $B$  is the reward for paying interest rate obligations.

The flow that the agent receives as the owner of the asset is

$$NS(EH, t, L_0, T, r) = \int_0^T (-rL_0 + \Theta)e^{-rt} dt + E_0[H_T - L_0 + B]e^{-rT} \quad (2)$$

where  $r$  is the loan interest rate and the risk-free interest rate.

The present value of that the agent receives if he stops paying at time  $t^*$

$$S(EH, t, L_0, T, r|t^*) = \int_0^{t^*} (-rL_0 + \Theta)e^{-rt} dt + \int_{t^*}^T (\Theta - c(t))e^{-rt} dt \quad (3)$$

where  $c(t)$  is the cost of stopping and becoming a renter. Subtracting (3)-(2) to obtain  $E\pi$  the expected payoff the agent will maximize

$$\max_{\{t^*\}} E\pi(EH, t, L_0, T, r|t^*) = \int_{t^*}^T (rL_0 - c(t))e^{-rt} dt + (L_0 - B - E_{t^*}[H_T])e^{-rT}$$

Alternatively, the problem can be rewritten as a binary choice. One alternative corresponds to stopping the process and taking the termination payoff, and the other entails continuation to the next period, where another binary decision will be present. In this setup, stopping corresponds to becoming a renter and therefore incurring a cost  $C$  —present value of  $c(t)$ — while continuation corresponds to remaining an owner and continuing to pay the financial obligation.

$$rF(H, t) = \max \left\{ -rC, -rL_0 + \frac{1}{dt}E[dF] \right\} \quad (4)$$

The agent will decide to maximize the value of  $F(H, t)$  subject to the end of period condition, the asset price dynamic and the initial conditions. The asset follows a standard Brownian motion where  $\alpha$  is the asset price growth and  $\sigma$  is the asset price volatility.

$$F(H, T) = H_T - L_0 + B$$

$$dH = \alpha H dt + \sigma H dz$$

and

$r, H_0, B, L_0$  and  $C$  are given.

### 3.2 Neighbors effect

In the presence of neighbors effect, the reward  $B$  received at the end of the period depends on the number of neighbors that stop paying ( $n$ ). We assume that the higher the  $n$ , the lower the  $B$ . This assumption has a number of interpretations. For example, we can interpret this effect as the impact of foreclosure on the sale price.

The agent will maximize a problem similar to (4) but  $B$  will be specified as follows

$$B = \begin{cases} 0 & \text{if } n \geq 1 \\ \bar{B} & \text{if } n = 0 \end{cases}$$

## 4 Numerical solution

This section presents the numerical solution and simulations of the optimal stopping problem.<sup>5</sup>

### 4.1 Optimal default

The problem (4) is solved numerically. The solution begins at the terminal period in the tree and is obtained by solving backwards. At each node, the agent decides to stop paying if the expected early termination payoff is higher than expected future value of continuing. Following Cox, Ross, and Rubinstein (1979), the continuous asset process is approximated by a discrete random walk. In this framework, the asset return may take one of two possible values ( $u, d$ ) with the probability  $p$  ( $1 - p$ ) of the asset moving up (down). The parameters

---

<sup>5</sup>For the numerical solution to financial derivatives see Wilmott, Howison, and Dewynne (1999).

are defined as

$$\begin{aligned}
 d &= \frac{1}{u} \\
 u &= \exp(\sigma\sqrt{\delta t}) \\
 p &= (\exp(r \cdot \delta t) - d)/(u - d)
 \end{aligned}$$

where  $\delta t$  is the time step. In the discretization, the end of period payoff is

$$F_T^m = EH_T^m - L_0 + B$$

where  $F_T^m$  denotes the  $m$ -th possible value at time step  $T$ ,  $EH_T^m$  is the expected asset price,  $L_0$  is the principal payment and  $B$  is the reward. The optimal value is the maximum between the two possibilities: the early termination payoff or the expected value in the next period.

$$F_n^m = \max(-C, e^{-r\delta t}(-rL_0 + pF_{n+1}^{m+1} + (1-p)F_{n+1}^m)), n = 0, 1, \dots, T$$

Denote  $H^*$  as the threshold price, the asset price where the agent is indifferent to paying or stopping. The asset values above  $H^*$  will induce the agent to stay in the game. It is also convenient to define  $H^U$  as the underwater price —asset price is equal to the current liabilities plus the cost of stopping. Notice that  $H^U$  and  $H^*$  are not necessarily constant over time. The threshold price is usually smaller than the underwater price  $H^* < H^U$  because the agent places a value on the foregone opportunity of stopping later.

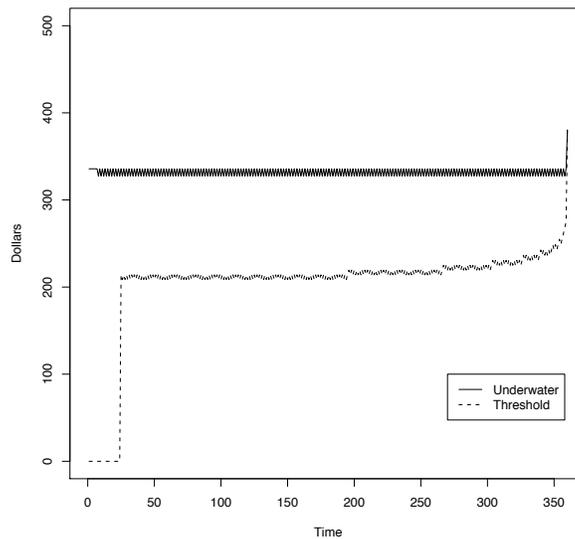


Figure 1: Optimal threshold ( $H^*$ ) and underwater price ( $H^U$ )

Using the following parameters,  $T = 360$ ,  $H_o = 400$ ,  $LTV = 100\%$ ,  $C = 60$ ,  $B = C$ ,  $r = .0006$  and  $\sigma = .0025$ ,  $H^U$  and  $H^*$  are depicted in Figure 1. The loan interest rate and the discount rate are equal and therefore the underwater line is constant. As  $H^*$  approaches  $H^U$  the value of waiting decreases. The difference between the two depends on the volatility of the asset price. Higher volatility implies a larger difference.

## 4.2 Simulations

In order to check the robustness of the fact that the threshold price  $H^*(t)$  is the asset value that maximizes the agent's expected payoff this section provides simulations of players that follow different stopping rules. The simulated players decide to stop paying as soon as the random realization of the asset value crosses the price  $H^S(t)$ , which is computed as follows

$$H^S(t) = aH^U(t) + (1 - a)H^*(t) \text{ where } 0 \leq a \leq 1$$

Alternatively, the simulated players can stop at lower asset values such that

$$H^S(t) = bH^*(t) \text{ where } 0 \leq b \leq 1$$

In other words, the first group of players follows a rule that is a combination of  $H^U$  and  $H^*(t)$ . When  $a = 1$  the agent decides to stop paying as soon as the random realization of the asset value crosses the underwater price. The value of  $a = 0$  corresponds to the optimal strategy. The players  $0 \leq a < 1$  can be interpreted as impatient. They decide to stop early. The remainder of players wait longer. In the extreme case  $b = 0$  the player does not stop paying.

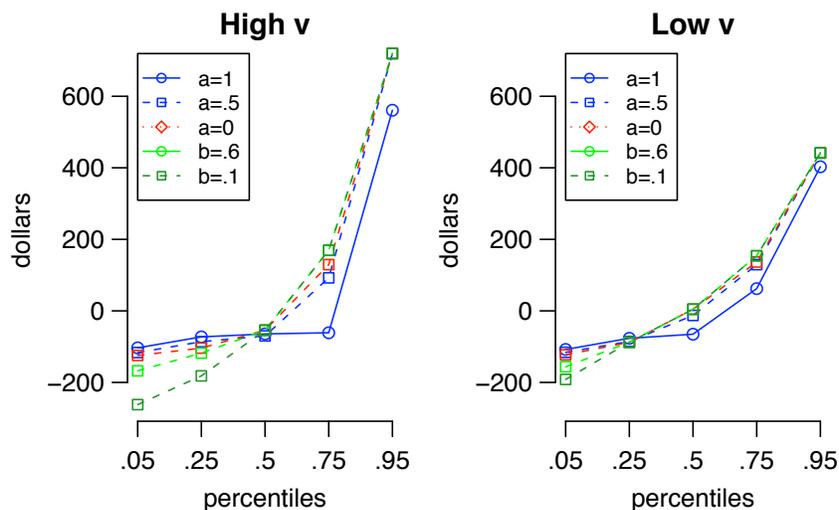


Figure 2: Quantile payoffs for the simulated players

Figure 2 shows the quantile payoffs after 5000 simulations with parameters similar to the previous figure but varying the volatility ( $\sigma_{low} = .025$  and  $\sigma_{high} = .04$ ). Some features are important to discuss. First, notice the asymmetry in the payoff distribution. The asymmetry is sharper in the high volatility treatment. Second, the impact of substantial departures from the optimal threshold (deviations in some directions, but not all) is not detectable. In this environment, the agent may wait longer than optimal. Third, it takes time to observe optimal behavior. It is necessary to run a large number of simulations to notice a payoff differential.

## 5 Experimental design and hypotheses

The experiment has four treatments ( $2 \times 2$  design). The first level corresponds to volatilities ( $v = \text{low, high}$ ) and the second level is associated with the presence of neighborhood effects (dependent or independent).

### 5.1 Hypothesis

$h_{\tau,v}^j$  is the subject's stopping asset price at time  $\tau$  where  $j$  refers to the treatment with dependent (DEP) or independent (IND) bonus and  $v$  refers to the volatility environment.

**Hypothesis 1.** *Observed stopping price has the same ordinal rank across treatments as does the theoretical price. Therefore,*

$$h_{\tau,high}^{IND} < h_{\tau,low}^{IND}$$

and

$$h_{\tau,high}^{DEP} < h_{\tau,low}^{DEP}$$

The observed stopping prices for the high volatility treatments are predicted to be lower than the observed stopping prices for the low volatility treatments since the value of waiting is higher in the former case. It is optimal to wait longer to default.

**Hypothesis 2.** *In each treatment  $(j, v)$ , the observed stopping price is equal to the theoretical stopping price.*

This prediction assumes that subjects follow the same threshold in the decision to stop. However, notice that in the case a subject decides to stop in the dependent treatment, it is more likely that the neighbor also decides to stop due to absence of the bonus, which leads to the next prediction.

**Hypothesis 3.** *Observed stopping price in the independent treatment is equal to or lower than the observed stopping price in the dependent treatment. Therefore,*

$$h_{\tau,high}^{IND} \leq h_{\tau,high}^{DEP}$$

and

$$h_{\tau,low}^{IND} \leq h_{\tau,low}^{DEP}$$

## 5.2 Implementation

Figure 3 shows the screen observed by each subject. At the beginning of each period—there are 70 in total, the subject is endowed with a base payment and owns an asset with value  $H$  that has been acquired with a LTV equal to 100 percent. The asset evolves according to the discrete binomial approximation of the Brownian motion described above. The liabilities are constant and equal to the initial value of  $H$ . They are depicted with a blue line. At the end, the subject can observe whether the bonus is present (blue bar) as well as the value of the quit fee (red bar). When the subject presses the space bar, she earns the base points minus the sum of the quit fee and the interest payments. Even after stopping, the subject can observe the black H-line evolving until the end of the game.

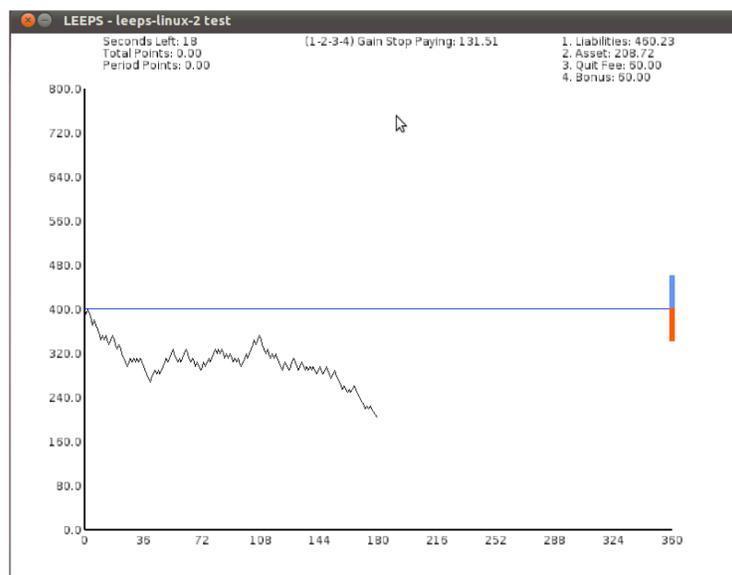


Figure 3: Screen - independent treatment

In case the subject does not stop paying, she pays the principal and the interest payments and earns the base, the asset and the bonus—conditional on the treatment group. The payoffs are depicted with a green bar.

In addition to the graphical display, the experimental software shows the numerical values of the gain from stopping, the payoff received in the current period and the cu-

mulative earnings. The gain is computed as the difference between the liabilities and the sum of asset, cost and bonus. The user interface allows each subject to view her previous decisions and earnings at any time.

The baseline parameters are  $T = 360$  (36 seconds),  $H_0 = 400$ ,  $r = .0006$  and  $C = 60 = B$ . I work with  $\sigma_{low} = .0025$  and  $\sigma_{high} = .004$  that correspond to  $(p = .506; u = 1.025)$  and  $(p = .498; u = 1.04)$ , respectively.

The subjects were 100 undergraduate students at the University of California, Santa Cruz. At the beginning of the 10 sessions, each subject was seated at a visually isolated computer terminal and assigned to a treatment (e.g. low volatility and dependent bonus). Instructions were read aloud and the software was displayed on a screen. The binomial parameters for the chosen treatment were explained and written on a white board. Subjects participated in four practice periods. Each subject then participated in 70 paid periods with no change in treatment. Sessions lasted 80 minutes each.

A total of 34 subjects participated in the low and dependent treatment, 36 in the low and independent treatment, 16 in the high and dependent treatment and 14 in the high and independent treatment. No subject was allowed to participate in more than one session. A subject with cumulative payoff over all periods received cash at the end of the session. Subjects also received a \$ 5 bonus show-up fee. On average subjects received \$ 16.25 in low volatility and \$15.76 in high volatility.

## 6 Results

Table 1 shows the experimental results. It contains the number of subjects per treatment, the total number of periods per treatment, and the fraction of periods in which subjects stop compared to the total periods. It is noteworthy that the low stopping decision observed in the data yields a known source of statistical bias. A stopping decision is more likely to be observed when subjects choose a high level of price, and therefore, the observed decisions constitute an upwardly biased sample. Furthermore, in a number of situations there is no stopping since the random asset price does not go below the underwater line. To mitigate this problem, a subsample of data was selected. The subsample data consist of observations where the asset crossed 60 percent of the optimal threshold value.<sup>6</sup> Considering only the subsample, the censoring is reduced by 30 percent in each treatment —though it is still significant in the low independent treatment. Note that a large number of observations is lost, but such action is required to overcome the censoring bias.

There is some evidence that players follow a threshold rule that triggers stopping. Conditional on stopping, Figure 4 depicts the cdf gap between the stopping asset price

---

<sup>6</sup>If I consider a greater subsample, the censoring problem is still significant making any inference invalid.

Table 1: Stopping decision

Treatment	All			Subsample		
	Stopping (%)	Obs	Subjects	Stopping (%)	Obs	Subjects
Low Dependent	26	2196	34	77	22	18
Low Independent	23	2198	36	60	20	16
High Dependent	41	1105	16	82	110	16
High Independent	37	968	14	90	98	14

observed and the minimum asset price experienced by the subject during a period prior to stop. For the high independent treatment, around 40 percent of the stopping decisions are made when the gap is equal to zero and the corresponding median is equal to 7. For the high dependent treatment, the percentage is higher compared to the independent treatment (70 percent) and the median is equal to 8. Notice that this analysis will be much more accurate in the case where the optimal threshold is constant over time. If the analysis is restricted to ticks in which the optimal threshold does not change dramatically, the share of the stopping decisions when the gap is zero increases.

Figure 5 follows the previous analysis but in terms of ticks. Conditional on stopping, the median gap is equal to 4 in the high independent treatment and 5 in the high dependent treatment.

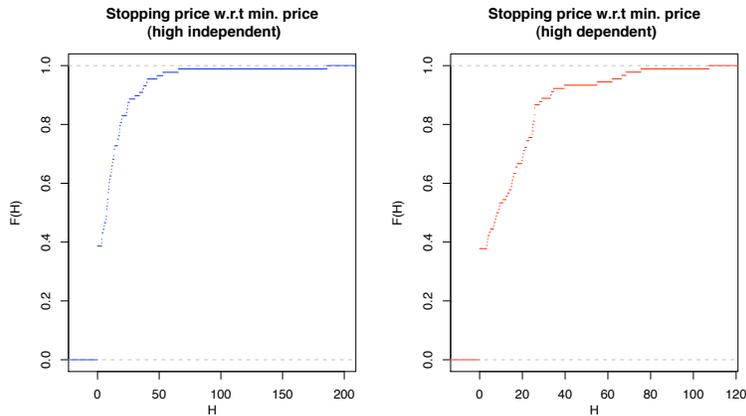


Figure 4: CDF for subsample stopping data

The rest of this section estimates the stopping prices observed considering the censoring problem described above and tests the hypotheses using non parametric as well as parametric tools.

The Product Limit (PL) estimator is used to establish a distribution of asset prices at which the subjects stop.<sup>7</sup> The PL estimator is suitable for censored data. Generally, exam-

<sup>7</sup>See Kaplan and Meier (1958).

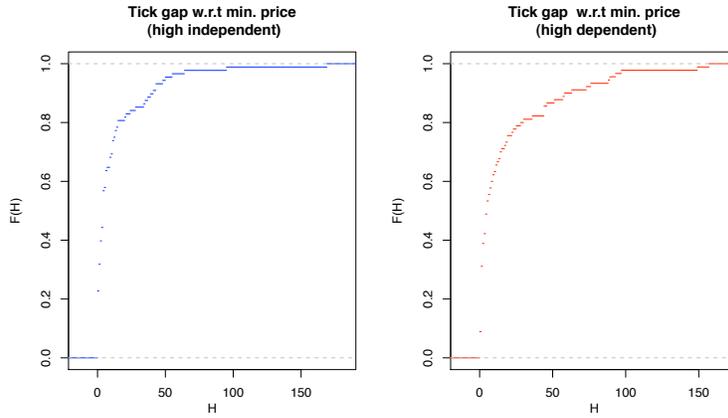


Figure 5: CDF for subsample stopping data (ticks)

ples in economic and biomedical literature deal with right-censoring. In this situation, the distribution is left-censored. Stopping prices are not observed if the random price does not approach the subject’s threshold that triggers a stop. The solution, however, is straightforward. The left-censored data can be transformed by subtracting the stopping price from a sufficiently large number such that the censoring observed is from the right.

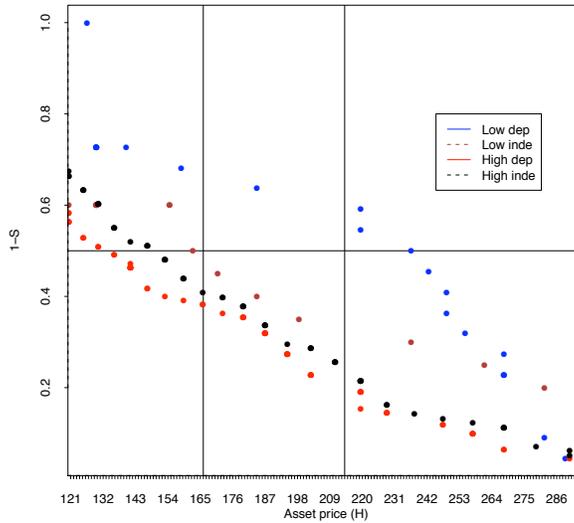


Figure 6: Survival distribution for subsample data

The PL estimator is used in two ways. First, the PL estimates —and standard errors— are constructed using pooled data across subjects. Using the log-rank test, I test for the first order stochastic dominance of the estimated stopping price by treatment. Additionally, given the standard errors from the PL estimation, I examine whether the median stopping price follows the theoretical prediction. The estimates assume i.i.d observations. To the

extent that different subjects behave differently and that they form pairs in the dependent treatment, the assumption is violated and the standard errors are likely to be understated. To control for within-subject dependence, a PL median estimate is constructed for each individual subject and tests are performed on these “by-subject” samples. Such observations are completely independent without the presence of neighbors effect. Therefore the hypotheses tests conducted on them, which depend only on between-subject variation, are rather conservative. All tests are performed at the 5 percent significance level unless otherwise indicated.

Figure 6 shows the PL estimator using pooled data. It is convenient to read the graph from right to left. Recall that the initial loan value is equal to 400. As long as the price is lower than 400, the stopping decision is observed. The median stopping price for the low dependent treatment is 237, which is much higher than the low independent treatment (162) and the high dependent and independent treatments (130 and 147, respectively).

Table 2: Stopping prices: Mean and standard deviation

	Low Dep.	Low Ind.	High Dep.	High Ind.
Pooled	236.53 ± 3.84	162.52 ± 3.39	130.40 ± 5.74	147.04 ± 6.64
By subject	198.24 ± 14.7	186.21 ± 15.1	148.24 ± 11.3	164.35 ± 14.3

Note: The median optimal thresholds for the high and low volatility are 166 and 214, respectively

Table 2 shows the mean stopping prices and the standard deviation. It shows higher stopping prices for the high volatility treatment compared to the low volatility treatments. Before testing rigorously the theoretical predictions, it is convenient to present the parametric analysis and then summarize the overall results.

Table 3: Tobit estimation (pooled data: subsample)

Dependent variable: Stopping price	
Coefficient	Value (s.d)
Constant	170.1*** (7.08)
Low	64.81*** (12.65)
Dependent	-3.25 (9.62)

Robust standard errors considered

\*\*\* Significant at 5% significance

Regarding the parametric analysis, Table 3 shows a Tobit regression using pooled data. In this case, the dependent variable is the stopping price and the independent variables are dummies that capture the treatment effects. Robust standard errors are considered in the

regression. Notice that Low treatment is significant meanwhile the Dependent treatment is not.

Next, I present the non-parametric and parametric tests of the predictions.

**Result 1.**

- Using the log-rank test and pooled data, the null hypothesis of  $h_{\tau,high}^{DEP} = h_{\tau,low}^{DEP}$  is rejected in favor of hypothesis 1 and I fail to reject the null hypothesis  $h_{\tau,high}^{IND} = h_{\tau,low}^{IND}$ .
- Using the parametric regression and pooled data, the null hypothesis of  $h_{\tau,high} = h_{\tau,low}$  is rejected in favor of hypothesis 1.

**Result 2.**

- Using the log-rank test and pooled data, we reject that the median observed stopping price  $h_{\tau,low}^{IND}$  is greater than 262.<sup>8</sup> Furthermore, we fail to reject that the median  $h_{\tau,low}^{DEP}$  is equal to the theoretical prediction.
- Using the Wilcoxon T test on the “by-subject” sample, we fail to reject that the median stopping price  $h_{\tau,high}^{IND}$  and  $h_{\tau,high}^{DEP}$  are equal to the theoretical predictions.

**Result 3.**

- Using the log-rank test and pooled data, the null hypothesis of equal distributions  $h_{\tau,high}^{DEP} = h_{\tau,high}^{IND}$  is rejected at a 10 percent significance level and we fail to reject that  $h_{\tau,low}^{DEP} = h_{\tau,low}^{IND}$ .
- However, we fail to reject the null hypothesis of equal distributions  $h_{\tau,high}^{DEP} = h_{\tau,high}^{IND}$  under the “by-subject” sample.
- Using the parametric regression, we fail to reject any difference between the independent and dependent treatment.

## 7 Discussion

In this paper, I have analyzed the decision to default and found that the borrowers defer the decision to default in accordance with the theoretical predictions. These predictions are drawn from a simple model that captures the decision of switching between being a home owner and being a renter. In this environment, an asset, whose value is governed by

---

<sup>8</sup>Due to high censoring in this treatment, it is not feasible to construct the lower bound confidence interval.

a brownian motion, has been acquired with loan-to-value equal to 100% and the subject may stop paying the future financial obligations (interests plus principal) by incurring a fixed quit fee. The optimal solution is defined by a real deferral option. The higher the asset volatility, lower the asset value that triggers default.

The simulations indicates that it is not costly to deviate from the optimal solution in the case that asset volatility is low. Indeed, the experimental results show not enough stopping decision under this treatment.

The experiment also incorporates the impact of neighbors in the decision to default. There is only slight evidence of higher default rates in the treatment in which the decision of others affects the individual decision (dependent treatment). The neighbors effect is captured as a bonus at the end of the period whose value depends on the decision of others. It would be interesting to extend the impact of defaulting directly in the asset process.

More work is needed to fully understand which factors drive the decision to default. In particular, little is known about the real cost of default from the borrower's perspective. Having a better estimation of this variable, would allow us to better estimate how this default option is exercised. If this cost is indeed small, then it must be social norms that are driving the decision to wait longer to default.

## References

- Bajari, P., C. S. Chu, and M. Park, 2008, “An Empirical Model of Subprime Mortgage Default From 2000 to 2007,” *National Bureau of Economic Research. Working Paper 14625*.
- Bhutta, N., J. Dokko, and H. Shan, 2010, “The depth of negative equity and mortgage default decisions,” *Finance and Economics Discussion Series*, Board of Governors of the Federal Reserve System (U.S.)(2010-35).
- Campbell, J. Y., S. Giglio, and P. Pathak, 2009, “Forced Sales and House Prices,” *National Bureau of Economic Research. Working Paper. 14866*.
- Chan, S., M. Gedal, V. Been, and A. Haughwout, 2010, “The Role of Neighborhood Characteristics in Mortgage Default Risk: Evidence from New York City,” *Furman Center for Real State and Urban Policy. NYU. Working Paper*.
- Cox, J., S. Ross, and M. Rubinstein, 1979, “Option Pricing: A Simplified Approach,” *Journal of Financial Economics*, 7.
- Deng, Y., J. M. Quigley, and R. V. Order, 2000, “Mortgage Terminations, Heterogeneity and the Exercise of Mortgage Options,” *Econometrica*, 68(2), 275–308.
- Dixit, A. K., and R. S. Pindyck, 1994, *Investment Under Uncertainty*. Princeton University Press.
- Foote, C. L., K. Gerardi, and P. S. Willen, 2008, “Negative equity and foreclosure: Theory and evidence,” *Journal of Urban Economics*, 64(2), 234–245.
- Foote, C. L., and P. S. Willen, 2011, “subprime mortgage crisis, the,” in *The New Palgrave Dictionary of Economics*, ed. by S. N. Durlauf, and L. E. Blume. Palgrave Macmillan.
- Gerardi, K., A. H. Shapiro, and P. S. Willen, 2007, “Subprime outcomes: risky mortgages, homeownership experiences, and foreclosures,” *Federal Reserve Bank of Boston. Working Papers. 07-15*.
- Guiso, L., P. Sapienza, and L. Zingales, 2009, “Moral and Social Constraints to Strategic Default on Mortgages,” Working Paper 15145, National Bureau of Economic Research.
- Kaplan, E., and P. Meier, 1958, “Nonparametric estimation from incomplete observations,” *Journal of American Statistical Association*, (53), 457–481.
- Kau, J. B., D. Keenan, and K. Taewon, 1994, “Default Probabilities for Mortgages,” *Default Probabilities for Mortgages*, 35(3), 278–296.

- List, J. A., and M. S. Haigh, 2010, "Investment under uncertainty: Testing the option model with professional traders," *The Review of Economics and Statistics*, 92(4), 974–984.
- Manski, C. F., 1993, "Identification of Endogenous Social Effects: the Reflection Problem," *Review of Economic Studies*, 60(3), 531–42.
- Oprea, R., D. Friedman, and S. T. Anderson, 2009, "Learning to Wait: A Laboratory Investigation," *Review of Economic Studies*, 76(3), 1103–1124.
- Pennington-Cross, A., and G. Ho, 2010, "The Termination of Subprime Hybrid and Fixed-Rate Mortgages," *Real Estate Economics*, 38(3), 399–426.
- Vandell, K., 1995, "How Ruthless is Mortgage Default? A Review and Synthesis of the Evidence," *Journal of Housing Research*, 6(2), 245–246.
- White, B., 2009, "Underwater and Not Walking Away: Shame, Fear and the Social Manage- Underwater and Not Walking Away: Shame, Fear and the Social Management of the Housing Crisis," *Arizona Legal Studies Discussion Paper No. 09-35*.
- Wilmott, P., S. Howison, and J. Dewynne, 1999, *The mathematics of financial derivatives*. Cambridge.